Value, Size and Momentum Portfolios in Real Time: The Cross-Section of South African Stocks[1]

Ryans Bartens[2] and Shakill Hassan[3]

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[3] Corresponding author. Address: School of Economics, University of Cape Town, Private Bag, Rondebosch, 7701, South Africa. E.Mail: shakill.hassan@uct.ac.za

Value, Size and Momentum Portfolios in Real Time: The Cross-Section of South African Stocks *

Ryan Bartens, Barclays Capital, London†

Shakill Hassan, University of Cape Town‡

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Abstract

We implement a recursive out-of-sample method to examine anomalies-based ex-ante predictability in the cross-section of stock returns. We obtain a series of simulated out-of-sample returns, consistent with investors using only prior information when choosing predictor variables. We find that, by commonly used performance criteria, real-time trading strategies based on size, value and momentum effects would not consistently outperform a passive index of South African stocks – despite consistent in-sample excess returns. Our results suggest that the empirical relationship between the anomalous factors and cross-sectional average returns is unstable.

JEL Classification: G11; G12; G14; M41; C21

Keywords: anomalies; real-time predictability; long/short portfolios; emerging markets; South Africa

1 Introduction

Evidence that portfolios based on ad-hoc characteristics such as market capitalization, scaled-price ratios or recent past performance, earn returns which cannot be explained by systematic risk, implies violations of market efficiency

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‡Corresponding author. Address: School of Economics, University of Cape Town, Private Bag, Rondebosch, 7701, South Africa. E.Mail: shakill.hassan@uct.ac.za

("anomalies") in the following sense (Fama (1970)): stocks are not priced as discounted expected future cash flows, where the expectations take into account all available information and discounting uses rates consistent with risk as determined by an equilibrium asset pricing model.[1]

Such violations of stock market efficiency do not imply existence of abnormally profitable trading opportunities. The violation may be due, for example, to horizon risk or positive-feedback trading, and follows from the barriers to the risk-free replication of payoffs from primitive assets such as common stocks, as discussed in the literature on the limits to arbitrage (De Long, Shleifer, Summers and Waldman (1990); Shleifer and Vishny (1997); Abreu and Brunnermeier (2002); Barberis and Thaler (2003)). Moreover, the existence of persistent excess returns based on a fixed set of factors implies predictability. But evidence of in-sample predictability does not guarantee predictability which can be exploited in real time. This may be due to data snooping in the identification of the anomalies (Lo and MacKinlay (1990), Sullivan, Timmermann and White (2001), Conrad, Cooper and Kaul (2003)); or due to an unstable relationship between cross-sectional excess returns and the anomalous variables, limiting the predictive content of patterns identified in-sample (Bossaerts and Fohlin (2000)).[2]

Fama and French (1992) is a standard reference on the (in-sample) predictability of the cross-section of stock returns using size and scaled-price ratio effects and the profitability of trading strategies designed to exploit this predictability. Their sample consists of US stocks, from 1963 to 1990. For each year in the sample period, the stocks are sorted into deciles according to market capitalization (the measure of "size") and book-to-market ratio (the measure of "value"). They then measure the average return of each decile over the next year. The decile representing the smallest stocks earns an average monthly return 0.74 percentage points above the largest stocks decile; and the highest book-to-market ratio decile (the "value" stocks) earns an average monthly return 1.53 percentage points above the lowest book-to-market decile ("growth"

[1] The international literature documenting CAPM anomalies in the cross-section of common stocks is vast. The most prominent of these anomalies in US markets are the size effect, first documented by Banz (1981), the "value" or scaled-price ratio effects, introduced by Basu (1977), and "momentum" (Jegadeesh and Titman (1993)). The size and value effects motivated the three-factor model of Fama and French (1993, 1996). For surveys of US evidence see for example Shleifer (2000), Schwert (2003) and Cochrane (2005). The international evidence on the relationship between the same factors and the cross-section of stock returns is not always consistent with US evidence – particularly in emerging markets. In addition to Fama and French (1998), see Hawawini and Keim (1995, 1998); Claessens, Dasgupta and Glen (1998); Bossaerts and Fohlin (2000); and Kassimatis (2008). For discussions of the non-trivial econometric implementation difficulties see Roll (1977) and Bossaerts (2002).

[2] Davis, Fama and French (2000) observe that the effect of size in US data declined after the 1980s; Pastor (2000) finds that the size premium fluctuates significantly over time; Bossaerts and Fohlin (2000), analysing German data and using a sample period which does not overlap with the time period used to identify momentum, size, and scaled-price ratio effects in the US, find that momentum is insignificant, the book-to-market ratio has the opposite effect to what was found for US data (i.e. in Germany, stocks of firms with low book value relative to market value outperform stocks with high book-to-market ratios), and the size effect is temporary; Hawawini and Keim (1998) report further divergences across international data.

stocks). The substantial differences in average returns between the small and large capitalization portfolios, and between the large and small book-to-value portfolios, are not explained by differences in portfolio betas as defined by the Capital Asset Pricing Model (Sharpe (1964), Lintner (1965)) (CAPM henceforth).

The exercise in Fama and French (1992) reports the profitability of investment strategies based on knowledge of the entire sample. It ignores that at each portfolio formation date, the investor only has knowledge of the prior period. The observed stock price patterns in this prior period may reveal the existence of more profitable strategies, for that period, than the strategies which are most profitable on the basis of patterns in the full sample. As observed by Pesaran and Timmermann (1995) and Sullivan, Timmermann and White (1999, 2001), when evaluating out-of-sample performance the researcher has to recognize that the investor would have had access to a plethora of competing predictor variables (and strategies consisting of different ways to use such variables), in addition to those only subsequently found to have in-sample predictive power.

Cooper, Gutierrez, and Marcum (2005), henceforth CGM, propose a recursive out-of-sample method consistent with the idea that in real time, investors do not know in advance which (or which combination) of variables will be useful in predicting next period returns. They use US data to examine "whether a real time investor, with no prior belief in the efficacy of any specific strategy, would have discovered book-to-market, size, and momentum to be useful predictors of stock returns (...)" (CGM, p. 470). By two of three performance criteria, they find that the real-time portfolio does not outperform the index. By one criterion, the real-time portfolio outperforms the index, albeit by a substantially lower margin than the full-period results.

The literature on the cross-section of individual common stocks listed on the South African stock market (the Johannesburg Securities Exchange, henceforth JSE) shows the ex-post facto predictive power of market capitalization, price-to-earnings ratio, and one-year lagged returns ("momentum").[3] The direction of effects is consistent with US data, which is unusual for an emerging market (see Claeesens, Dasgupta and Glen (1998)). Low-capitalization stocks outperform large-capitalization stocks; stocks with high earnings-to-price ratios (i.e. high earnings yield) outperform stocks with low earnings-to-price ratios; and the stocks which performed best over the previous twelve months (winners) outperform the worst performers (losers). In all cases, the out-performance is not explained by the CAPM as the equilibrium model for covariance risk. In the South African case, size and the earnings-to-price ratio (in contrast to size and book-to-market in US studies) subsume other candidate characteristics in explaining the cross-section of returns (Robertson and van Rensburg (2004)). On the basis of past patterns in returns and firm characteristics, the ex-post optimal (in-sample) investment strategy would have consisted in selecting stocks, at each portfolio formation date, to have portfolios composed of: short positions

[3] See Achour, Harvey, Hopkins and Lang (1998), Fraser and Page (2000), van Rensburg (2001), Robertson and van Rensburg (2004).

on large capitalization stocks and long on small capitalization stocks; short on low earnings-yield stocks and long on high earnings yield stocks; and short on the worst performers over prior twelve months and long on best performers over the same prior period.

We apply the recursive out-of-sample simulation approach of Cooper, Gutierrez, and Marcum (2005), subject to modifications to reflect the different data set, and with a focus on the variables and investment strategies found to be most profitable in the South African stock market. To our knowledge, ours is the first application of this approach in a non-US data set. We examine whether an hypothetical investor with no advance knowledge of which strategies will earn excess returns, would have chosen the portfolios implied by the size, earnings yield, and momentum effects. The test for predictability consists in comparing the performance of a simulated real-time portfolio with a passive index.

We use a rolling in-sample window to select the portfolios that produce the simulated real-time returns. The best (and worst) performing trading rules are identified in-sample, and then employed in the immediately following out-of-sample period. (A total of 68 trading rules are examined in each of seven portfolio formation periods.) The in-sample window is rolled forward to identify a new set of trading rules, which are used in the following out-of-sample period. Repeating the process results in a time series of out-of-sample returns for the active portfolios. We use the mean return (which produces the same choices as terminal wealth), and Sharpe ratio as criteria to identify the best performing trading rules over each in-sample window, and run a set of simulations for each.

We find that the active portfolios are overwhelmingly comprised of two-way rules, with earnings-yield and size the most frequently (but not exclusively) used variables. The in-sample performance (calculated over an entire in-sample window) of the active portfolios reveals the following. Using the mean-return criterion, the "long portfolio" (based on the best performing rules) outperforms the market by an average of 65 basis points (bps) per month (compared to 55 bps for a similar analysis of US markets), with an average Jensen's alpha (Jensen (1968)) of 0.65 percent (compared to 0.56 for US evidence).[4] This excess performance is consistent throughout the in-sample period. The "short portfolio" (based on the worst performing rules) under-performs by an average of 74 bps per month (compared to 51bps for US evidence) and records a mean alpha of -0.74% (compared to -0.38 for US data). The results under alternative performance criteria are not qualitatively different, and overall indicate average monthly returns in the region of 140 bps from a combined long-short portfolio.

The out-of-sample results are however quite different. The passive index outperforms the active portfolio in most out-of-sample periods. The average out-of-sample monthly return of the long portfolio is lower than that of the passive index by one to seven basis points, depending on the performance criterion; generates negative alpha; and produces a lower Sharpe ratio than the passive index. The return on the short portfolio exceeds that of the index in some

[4] One basis point is equal to 1/100th of 1% (i.e. 100 bps corresponds to 1 percentage point). The comparisons with US evidence are based on the results in Cooper, Gutierrez, and Marcum (2005).

out-of-sample periods, although on average out-of-sample under-performance (statistically insignificant) prevails. In brief, the simulated real-time portfolios do not significantly outperform a passive index of South African stocks. Compared to US evidence (in CGM), our data reveals larger in-sample returns, but overall lower out-of-sample excess returns, strengthening the conclusion that in-sample predictability in the cross-section of stocks is an unreliable indicator of real-time returns.

CGM is one of few studies investigating exploitable out-of-sample predictability in the cross-section of stock returns. Another exception is Haugen and Baker (1996). The strategies Haugen and Baker (1996) find to generate excess returns through combinations of firm characteristics require monthly turnover in excess of 40 percent, which results in insignificant excess performance after transaction costs – even for the in-sample period (see Hanna and Ready (2005)). Moreover, the Haugen and Baker (1996) out-of-sample procedure is based on ordinary least squares, ignoring the statistical limitations associated with predictive regressions (see Hansen and Hodrick (1980), Stambaugh (1999), Ferson, Sarkissian and Simin (2003), Ang and Bekaert (2007)).[5] Using South African data, Achour, Harvey, Hopkins and Lang (1998) is the only study that includes a tentative out-of-sample test of the performance of stock portfolios based on size and scaled-price ratio effects. They find evidence of excess returns (relative to an index) out-of-sample. Their sample is however very limited. They use a single (and short) in-sample period, from 1993 to 1995; and the three-year window from 1996 to 1998 serves as the (single) out-of-sample period. It will be seen that conceptually, the out-of-sample test in Achour, Harvey, Hopkins and Lang (1998) can be understood as a single iteration in our procedure.

The remainder of the paper proceeds as follows. Section 2 provides a detailed explanation of the methodology, including the data set, basic definitions, the selection of trading rules, and the out-of-sample methodology. Section 3 presents in-sample and out-of-sample results. A brief discussion and the conclusion follow.

2 Data and methodology

2.1 Data and variables

The data set consists of internationally available monthly observations of the South African treasury-bill rate, common stock prices, and accounting data for 170 stocks listed on the Johannesburg Stock Exchange from July 1987 to June 2004, extracted from Datastream and I-Net Bridge.[6] The sample of stocks

[5] The time series literature on the out-of-sample predictability of aggregate stock market returns is richer. See for example Pesaran and Timmermann (1995), Stambaugh (1999), Sullivan, Timmermann and White (1999, 2001), Goyal and Welch (2003), Ang and Bekaert (2007).

[6] I-Net Bridge is the main local financial market data provider. It was used as a supplementary source. Resource sector stocks were excluded for consistency with previous studies in which the size, earnings yield and momentum anomalies were identified. This exclusion

includes only companies which were listed throughout the period, which creates a bias in favour of finding predictability. (Size and scaled-price ratio effects in particular, may be entirely attributable to this selection bias – see Brown, Goetzmann and Ross (1995).) Returns are adjusted for capital events and dividends.[7] The (South African) 91-day treasury-bill rate is the proxy for the risk-free rate, and the JSE All Share Index is used as a proxy for the market index.[8]

We conservatively confine the universe of variables to four. These are the three foremost predictor variables, as determined in the existing ex-post literature, namely size, earnings-yield, and lagged-returns (one year); and add one variable to the set of variables the investor has access to: beta (which has been shown to be subsumed by the other variables in explaining the cross-section of returns). This introduces another bias in favour of finding out-of-sample predictability. Evidently, the investor will be confronted with many more possibilities. But if there is no evidence of real-time predictability despite restricting the universe of variables to the three variables which, with hindsight are already known to have predictive power over the full sample, plus beta, adding more variables would only strengthen the (no predictability in real-time) result. It is not assumed however that the investor knows which investment strategies based on the four variables will generate excess returns in the future.

At each portfolio-formation date, the optimal portfolio is determined by the investment strategy which produced the highest return in the preceding period. Size (SIZE) for June t is defined as the market capitalization at the end of June t. One-year lagged returns (LAGRET), reflecting the momentum effect, for June t, is defined as the arithmetic average of the prior 12 month's returns (following Fraser and Page (2000)).[9] Earnings yield (ERNYLD) for June t is defined as earnings per share for the financial year-end t-1, divided by price as at calendar year end t-1. The variables are calculated so as to ensure that any accounting information used in their construction is dated between six and 18

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is motivated by the exceptional sensitivity of the resource sector to international commodity prices. See Achour, Harvey, Hopkins and Lang (1998), Fraser and Page (2000) and van Rensburg (2001). For comparison, in Claessens et al. (1998) the number of stocks in each individually studied market ranges from 22 (Colombia) to 137 (Korea). In Achour, Harvey, Hopkins and Lang (1998), the range goes from 43 (Mexico) to 157 (Malaysia).

[7] See Appendix A.

[8] The frequent reclassifications of the JSE in recent years necessitated the use of both the CI01 and J203 indices as market proxies (both were extracted from the INet Bridge database available at the commerce IT laboratories). The J203 index is not available prior to June 1995, hence the use of the CI01 index pre-June 1995. The return series for the two indices are both available for the period July 1995 to June 2002. A comparison of means test was conducted to determine if the series differed significantly. The result (p-value = 0.7589) indicates that the series are not statistically significantly different. Returns were calculated individually for these two indices, and the return series were simply dovetailed to form a single market return series.

[9] CGM, following Fama and French (1996), calculate one-year lagged returns from July t-1 to May t, excluding June t to mitigate bid-ask bounce. The calculation thus allows comparisons between the aforementioned studies. Similarly, it was deemed appropriate to follow the methodology of Fraser and Page (2000) in this paper, despite the possible introduction of bid-ask bounce.

months prior to June t. This conservative lag ensures that the hypothetical investor would have had access to the accounting data at the end of June t, the date of portfolio formation. These measures prevent the introduction of look-ahead bias.

Following CGM, a simple proxy for CAPM beta (BETA) is assigned in June t, and estimated using simple ordinary least-squares (OLS) regressions, employing the previous 60 months of data:[10]

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{m,t} - r_{f,t} \right) + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the return for stock i, $r_{f,t}$ is the risk-free rate proxy, and $r_{m,t}$ is the market return proxy, all in month t.

The JSE is subject to thin trading, which results in a downward bias for OLS beta estimation (Bradfield (1990)). Several correction procedures are available, the foremost of which are the 'trade-to-trade' approach and the Cohen-type estimators. Bowie and Bradfield (1993) find the trade-to-trade approach to be superior in terms of both efficiency and unbiasedness. However, the trade-to-trade approach is restrictive in terms of its data requirements and is thus difficult to implement in practice (Bowie and Bradfield (1993)).[11] The majority of practitioners use the Cohen-type estimator for the thinly-traded JSE (including Fraser and Page (2000)). The suggested form of the multivariate regression employed when using this estimation technique for the JSE uses leading, lagged and contemporaneous market return terms as independent variables. However, the inclusion of the lead market-return term makes this form of beta estimation inappropriate for this particular study. Real-time simulation precludes the use of lead terms since this information would not be available to the hypothetical investor, hence the utilization of simple OLS regression for BETA estimation. The use of a market capitalization-weighted proxy results in a smaller bias relative to equally weighted indices (Bradfield and Barr (1989)). In addition, the exclusion of delisted stocks, which are likely to be less well traded compared to listed stocks, tends to reduce the bias of the OLS beta estimates. Whilst the bias introduced via the use of OLS for beta estimation is acknowledged, the ranking procedure employed in this study reduces the importance of this bias, since less emphasis is placed on the actual magnitude of the beta estimates. As previously mentioned, pricing data is predominantly available as of mid-1990, resulting in initial beta estimates for June 1992 (owing to the minimum 24 months of historic pricing data used in estimation).

2.2 Out-of-sample methodology

2.2.1 Procedure

Cross-sectional sorts of the variables are used to determine the trading rules. (See Achour, Harvey, Hopkins and Lang (1998) and CGM on the limitations

[10] When historic data is not available for 60 months, we use the largest number of data points available, provided it is never fewer than 24 months.

[11] One of the more restrictive requirements is the need for the time when each trade occurred.

of regression as an alternative method for stock selection.) We rank shares according to each of the four variables, and split them into a specified number of groups based on the rankings. The trading rules are derived either from the groups themselves (where the trading rule is based on a single variable), or from combinations of groups (where the trading rules are based on more than one variable). The key to this simulation is an investor with no a priori beliefs.[12] We evaluate the universe of trading rules over a sample with full information (the in-sample period). The best (and worst) performing trading rules are selected to form active portfolios, which represent the investment strategy that has been ex post identified as the most successful. These successful strategies are then evaluated out-of-sample.

Since the rules are identified purely empirically, they may change over time. The methodology allows for this by employing a rolling window. The best (worst) performing rules are identified in-sample, and then employed in the immediately following out-of-sample period. The in-sample window is shifted forward to identify a new set of trading rules, which are used in the subsequent out-of-sample period. This process is repeated and results in a series of out-of-sample periods for which we have empirically determined portfolios. The out-of-sample performance of these portfolios is compared with a passive benchmark to determine whether the cross-section of returns is predictable. At the end of June of each year t, we rank stocks in ascending order according to each of the four variables, and then split them into three groups per variable. For a stock to be considered in a particular year, it must have data for all four variables in that year. This results in a minimum of 90 stocks in June 1992, and a maximum of 170 stocks in June 2003.[13] There are a total of 12 groups across the four variables (3 groups per variable), and it is from these groups that we choose the trading rules. We consider one-way and two-way trading rules.

2.2.2 Trading rule definitions

A one-way rule is the directive to purchase all stocks that occur in a single group of a particular variable. Examples of one-way trading rules include: "purchase all stocks that occur in the small SIZE group", or "purchase all stocks that occur in the middle ERNYLD group". Since there are 12 groups in total, there are 12 one-way trading rules. A two-way trading rule is the directive to purchase all stocks that occur simultaneously in two groups. Only rules that combine two groups from different variables are considered. Rules that combine two groups of the same variable are ignored since it is impossible for any stock to fall into this category.[14] Examples of two-way trading rules include: "purchase

[12] The fact that only four variables have been included in the investor's rule universe implicitly assumes that he/she has prior beliefs vis-à-vis the efficacy of these variables, but the restriction is imposed for the express purpose of investigating the predictive nature, or otherwise, of these variables.

[13] A complete list of the 170 stocks considered in this study is available from the corresponding author.

[14] For example: "purchase all stocks that occur simultaneously in the small and large SIZE groups."

all stocks that occur simultaneously in the middle BETA group and the small ERNYLD group", or "purchase all stocks that occur simultaneously in the large LAGRET group and the small SIZE group". Given the definition of two-way trading rules, which excludes those rules that incorporate two groups from the same variable, there are 54 two-way rules. Two-way rules generally have fewer stocks than one-way rules due to the unlikelihood of two groups from different variables being comprised of exactly the same stocks. The total number of rules considered in each period is 66, being 12 one-way and 54 two-way rules.

2.2.3 In-sample window

The in-sample period is used to determine the investment strategy applicable in the out-of-sample period. CGM "employ a ten-year in-sample window as a reasonable trade-off between reducing error in the estimation of the relations between stock returns and (their) choice variables and permitting regime switches in those relations". However, the ten-year window affords very little weight to the 'new' period included at each iteration, resulting in investment strategies that change very little from one out-of-sample period to the next. Moreover, ten-year in-sample windows on the shorter data set for South Africa would result in an excessively short real-time return series. Conversely, if the window is too short we may fail to identify profitable patterns; and the sample period used for beta estimation becomes too small. To balance these concerns, we used a five-year window. (For comparison, Achour et al. (1998) use a (single) three-year in-sample period.) The out-of-sample period is the 12-month period immediately following the in-sample window.

2.2.4 Trading rule identification: LONG and SHORT portfolios

Once the stocks comprising each rule have been identified, the hypothetical investor formulates the active portfolios based on the in-sample performance of the trading rules.[15] The seven best performing rules during the in-sample window (approximately one-tenth) are selected to form the investor's LONG portfolio for the associated out-of-sample period. Similarly, the seven worst performing rules form the investor's chosen SHORT portfolio. Different criteria may be used to evaluate the in-sample performance of these trading rules. We assume the investor uses one of two performance criteria, namely mean monthly returns (or terminal wealth), or the Sharpe ratio (defined in Appendix B); and run a separate simulation for each criterion. The two performance criteria are used for each of the rules from the beginning of July t to the end of June t+1.

At the end of each year t of the in-sample window, the rules are ranked in descending order according to the performance criterion in question. The

[15] The one-way trading rule constituents are easily identified: ranking the stocks according to each of the 4 variables and then inserting breakpoints to give 3 groups per variable (and thus 12 groups in total) gives the constituents of the 12 one-way rules. The two-way rules are identified using an array formula in Microsoft Excel that combines the 12 groups in the manner described previously, identifying those stocks that occur simultaneously in two groups, resulting in the two-way rule constituents.

entire in-sample performance determines selection or otherwise for the active portfolios, therefore, each rule's ranks are summed over the five-year window. These cumulative in-sample ranks are used to determine the constituents of the active portfolios.

The rules that comprise the chosen LONG portfolio for the mean-return criterion are those that have the seven smallest cumulative ranks for this criterion over the five-year in-sample window, whilst those with the seven greatest cumulative ranks form the SHORT portfolio for the mean-return criterion.[16] The LONG and SHORT portfolios corresponding to the Sharpe-ratio criterion are formed analogously.[17] It is possible that a particular stock occurs in more than one of the seven rules selected to form one of the out-of-sample portfolios; this stock does not receive additional weighting in the active portfolio.

2.2.5 Simulation of out-of-sample returns

The in-sample window is rolled forward by one year and the process is repeated. An iterative application of this methodology results in a time series of out-of-sample returns for the active portfolios. To illustrate, consider the first in-sample window, which stretches from the beginning of July 1992 to the end of June 1997. The stocks are ranked at the end of June 1992 and split into three groups for each of the four variables. From the 12 groups derived at the end of June 1992, the 66 trading rules applicable from July 1992 to June 1993 are identified.[18] The returns for each of the 66 trading rules are calculated from the beginning of July 1992 to the end of June 1993. Once the monthly equally weighted returns to each rule have been calculated, the mean return, Sharpe ratio and terminal wealth values associated with each rule are calculated for July 1992 to June 1993. The stocks are ranked and split into groups again at the end of June 1993. Returns for the trading rules are calculated over the subsequent year, as well as values for each performance criteria.

We repeat this process for each of the five years in the in-sample window. The seven best-performing rules over the entire period July 1992 to June 1997 are selected to form the LONG portfolio for July 1997 to June 1998.[19] This is

[16] The rules are ranked in descending order according to mean monthly returns. Thus, the rules with the greatest mean-monthly-return values (i.e. best performing) have the smallest rank. Similarly, the best performing rules over the entire in-sample window will have the smallest cumulative ranks, owing to the initial sort that ranked the rules in descending order. In the event that two rules, when ranked according to their cumulative ranks over the in-sample period, jointly achieve either 7th or 59th position, the underlying criteria are compared to determine which rule is included in the portfolio. That rule which achieves either the highest or lowest cumulative value for the underlying criterion over the in-sample period is consequently included in the LONG or SHORT portfolio, respectively, for that criterion. This situation arises on five separate occasions.

[17] Larger Sharpe-ratios imply superior performance; hence the rules with the 7 smallest cumulative ranks form the LONG portfolio.

[18] The trading rules themselves remain unchanged from year to year, e.g. "purchase all stocks that occur in the small SIZE group" (one-way rule). However, the constituent stocks are determined by the ranking and thus may change over time.

[19] The best and worst-performing rules are derived from the ranking procedure described previously. We rank the stocks in descending order for each year of the in-sample window

the first out-of-sample period. Similarly, the SHORT portfolio is also formed, and returns to the two portfolios are calculated for the first out-of-sample period. Once this process is complete, the in-sample window is moved forward by one year. It now stretches from July 1993 to June 1998, and the LONG and SHORT portfolios are selected for the second out-of-sample period (July 1998 to June 1999). The entire process is repeated iteratively until a time series of out-of-sample portfolio returns emerges for the period July 1997 to June 2004.

Two sets of simulations are performed, one for each performance criteria, resulting in two sets of LONG and SHORT portfolio out-of-sample returns. The returns to the active portfolios are examined to determine whether predictability is evident.

2.2.6 Tests

We perform a batch of tests. The first test compares the performance of the LONG and SHORT portfolios to that of a passive benchmark. The benchmark is an equally-weighted portfolio (EW) comprised of all the stocks considered in the study. The performance of the portfolios is measured in three ways: mean monthly returns, Jensen's alpha and Sharpe ratio. Three measures are employed due to the lack of a definitive portfolio performance appraisal technique, and the three measures consider both raw (mean monthly returns) and risk-adjusted (Jensen's alpha, Sharpe ratio) returns.

Equally weighted monthly returns for each of the LONG and SHORT portfolios are compared with those of the EW portfolio. Predictability is evident if the LONG portfolio's mean return exceeds that of the EW portfolio, or the return to the SHORT portfolio is less than that of the EW portfolio. Jensen's alpha is estimated by independently regressing the excess returns of the LONG and SHORT portfolios against the excess returns of the EW portfolio. The OLS regression is of the following form:

$$r_{A,t} - r_{f,t} = \alpha_A + \beta_A \left(r_{EW,t} - r_{f,t} \right) + e_{i,t}, \tag{2}$$

where $r_{A,t}$ is the equally weighted monthly return for active portfolio A; $r_{EW,t}$ is the monthly return to the EW index; and α_A is Jensen's alpha for portfolio A.

A Jensen's alpha figure is estimated for every LONG and SHORT portfolio, for each out-of-sample period. If the mean Jensen's alpha for the LONG portfolio is greater than zero, or that of the SHORT portfolio is less than zero, the implication is that the cross-section of stock returns on the JSE is predictable ex ante. A Sharpe ratio is estimated for every LONG and SHORT portfolio in

according to each of the three performance criteria. The ranks associated with a performance criterion for a particular rule are summed over the five years of the relevant in-sample window. For example, the five mean-return ranks for rule 34 are summed over the in-sample window period to give a cumulative rank for the mean-return of rule 34. These cumulative ranks determine the best and worst performing rules; the smaller the cumulative rank, the better the performance, and vice versa (owing to the descending sort employed to rank the performance criteria).

each out-of-sample period. The mean Sharpe ratio for the active portfolio is compared with the mean Sharpe ratio for the EW index. Out-of-sample predictability is manifest if the Sharpe ratio of the LONG portfolio exceeds that of the EW index, or the Sharpe ratio of the SHORT portfolio is less than that of the EW index. We obtain the returns from a long-short COMBINED portfolio by subtracting the returns of the SHORT portfolio from those of the LONG portfolio. The COMBINED portfolio is used to test for evidence of predictability by comparing its mean monthly return and Jensen's alpha with zero. A positive value for either of these variables is indicative of predictability. Note that, in practice, the scope for investors to fund long positions with the income from short sales may be limited.

3 Results

3.1 Rule Compositions of LONG and SHORT portfolios

Overwhelmingly, the active portfolios are comprised of two-way rules (approximately 92% of total selected rules), particularly under the mean-return criterion (93.88% compared to 89.80% for the Sharpe ratio). As expected, given the existing literature, ERNYLD and SIZE were the most frequently employed variables, each featuring in approximately 52% of rules. LAGRET was used in approximately 48% of rules. BETA was present in 39% of total rules.

Table 1

Mean Groups by Return Criteria for the Active Portfolios

	Mean Groups Selected			
	BETA	ERNYLD	LAGRET	SIZE
LONG Portfolio				
Mean-Return Criterion	1.84	2.70	2.61	1.69
	(0.93)	(0.60)	(0.49)	(0.82)
Sharpe-Ratio Criterion	1.35	2.90	2.32	1.55
	(0.76)	(0.30)	(0.65)	(0.89)
SHORT Portfolio				
Mean-Return Criterion	2.16	1.52	1.41	2.12
	(0.59)	(0.58)	(0.62)	(0.64)
Sharpe-Ratio Criterion	1.95	1.68	1.32	2.03
	(0.72)	(0.55)	(0.47)	(0.61)

Table 1 shows the mean group selected by the performance criteria for the active portfolios, where "1" is assigned to the small group and "3" to the large (standard deviations indicated in parentheses).[20] The LONG portfolios, under both performance criteria, tend to be characterized by large ERNYLD and large LAGRET stocks. The composition of the portfolios is less consistent with respect to BETA and SIZE (given the average means and large standard

[20] Lists of the individual rules comprising the mean-return and Sharpe-ratio active portfolios are available from the authors on request.

deviations). The Sharpe-ratio LONG portfolios show a more definite tendency towards large ERNYLD stocks, but are less conclusively composed of large LAGRET stocks, relative to the mean-return LONG portfolios. The chosen SHORT portfolios are characterized predominantly by small LAGRET stocks, particularly under the Sharpe ratio. The tendency towards small ERNYLD stocks is less distinct, but evident under both performance criteria. Although SIZE is used frequently in portfolio construction, notice that the average size of stocks in the SHORT portfolios is only slightly larger than the average size of stocks in the LONG portfolios, suggesting that the size effect is not consistent. The same observation applies to the simple proxy for beta.

3.2 In-sample results

3.2.1 Mean-return criterion

Figures 1 and 2 show the market-adjusted in-sample returns to the mean-return LONG and SHORT portfolios, respectively. The return illustrated in a particular year is calculated over an entire five-year in-sample window, with the year on the horizontal axis reflecting the last year of the in-sample window. The monthly equally weighted returns for the active portfolios are adjusted by subtracting the contemporaneous monthly equally weighted returns to the EW index. For example, the return figure represented at 1997 in Figure 1 is the average of the monthly returns to the mean-return LONG portfolio, for the period July 1992 to June 1997, less the average of the monthly returns to the EW index, for the same period.

The in-sample excess performance of the active portfolios under the mean-return criterion is evident: the LONG portfolio outperforms the market by an average of 65 bps per month in terms of raw returns. This performance (see Figure 1) is consistent throughout the in-sample period with the lowest mean monthly in-sample returns recorded in 1999 (49 bps above monthly market returns). The excess returns are not due to higher risk: the average alpha of the mean-return LONG portfolio is 0.65% per month. The SHORT portfolio (Figure 2) under-performs by an average of 74 bps per month (minimum 56 bps in 1997) and records a mean alpha of -0.74%. In brief: under the mean-return criterion, the anomalies-based active portfolios easily outperform the market over the in-sample period, in raw returns, and on a risk-adjusted basis.

Figures 1 - 4

Market-Adjusted In-Sample Returns, LONG & SHORT Portfolios

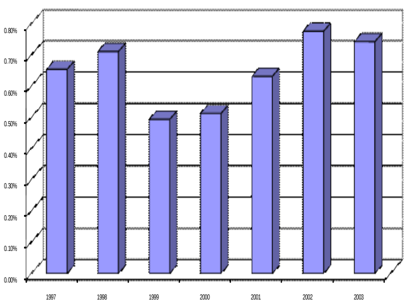

Figure 1: LONG, Mean-Return

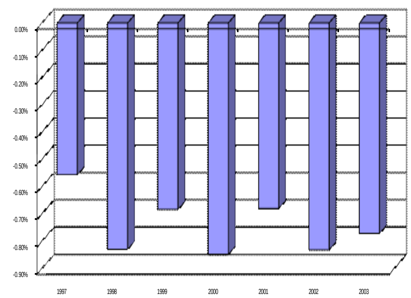

Figure 2: SHORT, Mean-Return

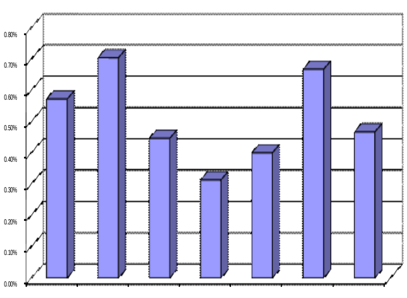

Figure 3: LONG, Sharpe-Ratio

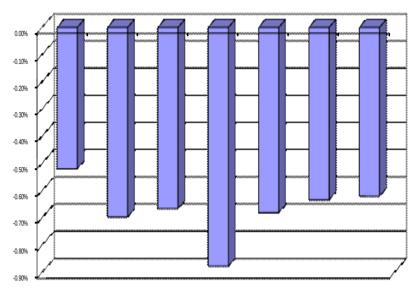

Figure 4: SHORT, Sharpe-Ratio

3.2.2 Sharpe-ratio criterion

Figures 3 and 4 show the market-adjusted in-sample returns to the Sharpe-ratio LONG and SHORT portfolios, respectively. The LONG portfolio earns an average monthly return of 51 bps in excess of the EW index, and has an alpha of 0.54%. The SHORT portfolio earns on average 67 bps less than the EW index, whilst the Jensen's alpha for the SHORT portfolio is -0.69%. As with the mean-return simulation, the Sharpe-ratio active portfolios easily surpass the EW index both in terms of raw and risk-adjusted performance. The performance differs marginally between the two simulations, with the mean-return portfolios recording better mean monthly returns and alphas. By any of these criteria however, the in-sample portfolios substantially and consistently out-perform.

3.3 Out-of-sample results

3.3.1 Mean-return criterion

Figure 5 contrasts the average monthly returns of the in-sample and real time (out-of-sample) portfolios, using the mean-return criterion. By construction, the in-sample returns should display less variability than the out-of-sample returns (the in-sample returns represent averages calculated over a five-year period whereas the out-of-sample returns represent averages calculated over a one-year period). Indeed the increased out-of-sample variability is graphically evident, but the general out-of-sample performance is in stark contrast with that exhibited in-sample. In all but the first period, the returns to the LONG portfolio deteriorate out-of-sample. The passive index outperforms the active portfolio in four of the out-of-sample periods (the market-adjusted return in 2002 is marginally negative at -2 bps). The mean market adjusted out-of-sample return performance is evident from the figure below. The average out-of-sample monthly return of the EW index exceeds that of the mean-return LONG portfolio by one basis point. If the first out-of-sample period is excluded, the average market-adjusted return drops to -18 bps, compared with an in-sample mean of 65 bps.

The in-sample and out-of-sample returns to the mean-return SHORT portfolio are illustrated in Figure 6. As with the LONG portfolio, the first out-of-sample period produces better returns than the associated in-sample period (albeit the differential is not as large in the case of the SHORT portfolio) and increased variability is evident out-of-sample. The SHORT portfolio return exceeds that of the EW index in four of the seven out-of-sample periods, but on average out-of-sample under-performance prevails. (The average market-adjusted out-of-sample under-performance is ten bps per month, falling to two bps with the exclusion of the first period, compared to an in-sample mean of -74 bps.)

Figures 5 - 8
Market-Adjusted In- and Out-of-Sample Returns
Light/Blue: In-Sample; Dark/Red: Out-of-Sample

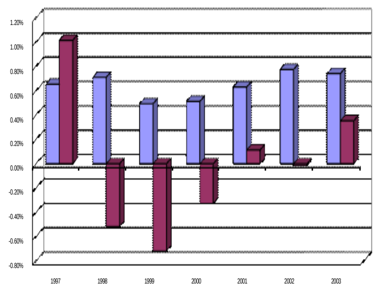

Figure 5: LONG, Mean-Return

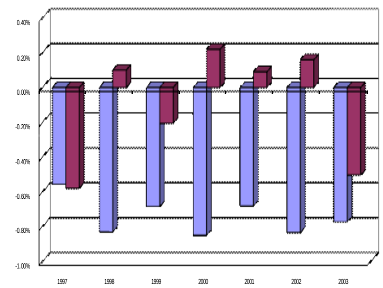

Figure 6: SHORT, Mean-Return

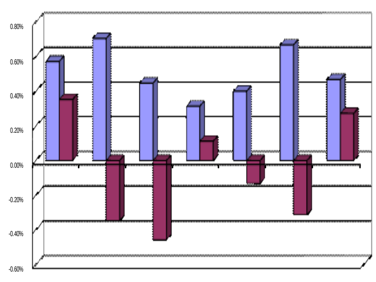

Figure 7: LONG, Sharpe-Ratio

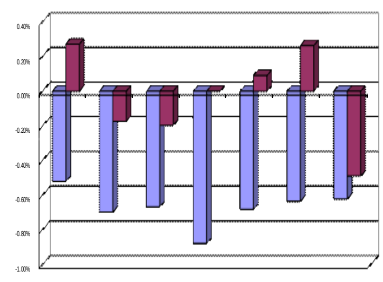

Figure 8: SHORT, Sharpe-Ratio

Table 2 shows the out-of-sample performance of the chosen portfolios in the mean-return simulation. The under-performance of the LONG portfolio (in raw returns) is substantiated by a negative alpha (-5 bps), and a Sharpe-ratio (0.38) that is less than that of the passive index (0.45). Notice that the out-of-sample mean returns of the SHORT portfolio under-perform relative to the passive index, indicating the possibility of out-of-sample predictability. In absolute terms, the risk-adjusted measures corroborate the suggestion of predictability with a negative alpha (-9 bps), and a Sharpe ratio of 0.36 compared with 0.45 for the passive index. However, note that not a single one of these results on out-of-sample predictability under the mean-return criterion is remotely statistically significant (including the negative market-adjusted mean returns – see Table 2).

Table 2
Out-of-Sample Performance Under Mean-Return Criterion

	Return*	Stand.Dev.	Alpha	Sharpe Ratio
EW	0.27	5.70	-	0.45
LONG	0.25	5.42	-0.05	0.38
SHORT	0.16	6.28	-0.09	0.36
COMBINED	0.09	3.38	0.04	-

*: mean monthly return, %

3.3.2 Sharpe-ratio criterion

The comparative returns of the Sharpe-ratio LONG portfolio are illustrated in Figure 7. In four of the seven out-of-sample periods, the active portfolio (based on past patterns in the cross-section), earns a lower out-of-sample return than the EW index. The average market-adjusted monthly return of -7 bps is lower than that obtained in the previous simulation. The risk-adjusted measures in Table 3 are consistent with the raw returns: Jensen's alpha is -13 bps and the Sharpe ratio is 0.37 (compared with a Sharpe ratio of 0.45 for the EW index). As with the mean-return simulation, the results for the Sharpe-ratio SHORT portfolio, in absolute terms at least, suggest real-time predictability: the market-adjusted monthly mean return is negative (-3 bps); alpha is negative (-10 bps); and the Sharpe ratio of the index (0.45) exceeds that of the portfolio (0.40). However, these results are not statistically significant (see Figure 8 and Table 3).

Table 3
Out-of-Sample Performance Under Sharpe-Ratio Criterion

	Return*	Stand.Dev.	Alpha	Sharpe Ratio
EW	0.27	5.70	-	0.45
LONG	0.19	5.31	-0.13	0.37
SHORT	0.23	6.27	-0.10	0.40
COMBINED	-0.04	3.34	-0.03	-

*: mean monthly return, %

3.3.3 COMBINED long-short portfolio

The in-sample and out-of-sample mean monthly returns for the mean-return COMBINED portfolio (LONG-SHORT) are illustrated in Figure 9. Following from the strong in-sample performance of the LONG and SHORT portfolios, the chosen COMBINED portfolio in this simulation records a positive mean monthly in-sample return of 139 bps, with a minimum of 118 bps in 1999. As with the mean-return LONG and SHORT portfolios, the first period is characterized by superior returns in the out-of-sample period. However, the subsequent performance is dismal; four of the seven periods produce negative returns. The mean monthly out-of-sample return and alpha of the COMBINED portfolio can be found in Table 2; the mean return of 9 bps (this drops to -16 bps if the first period is excluded) and the mean alpha of 4 bps (reduces to -19 bps if the first period is excluded) further demonstrate the reversal in performance experienced by the active portfolios. Whilst the overall mean return and alpha figures are positive (and thus indicative of predictability), they are not statistically significant.

Figure 10 depicts the in-sample and out-of-sample performance of the COMBINED portfolio in the Sharpe-ratio simulation. The performance appears inferior when compared with that of the mean-return COMBINED portfolio (which is expected given the LONG and SHORT portfolios both fared worse in the Sharpe-ratio simulation). The portfolio records negative mean monthly returns in four of the out-of-sample periods, and two of the three positive mean returns are minor (8 and 11 bps in 1997 and 2000 respectively). This is compared with the strong in-sample performance, averaging 118 bps per month with a minimum of 108 bps in 2001. Table 3 shows the mean monthly return for the entire out-of-sample period was -4 bps, and the risk-adjusted measure of alpha was -3 bps for the same period.

Figures 9 - 10
In- and Out-of-Sample Returns to Long-Short Portfolio
Light/Blue: In-Sample; Dark/Red: Out-of-Sample

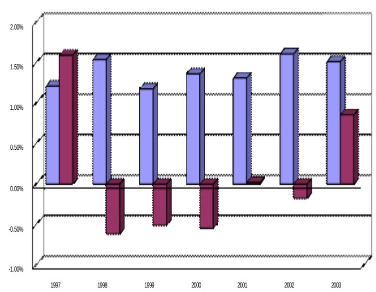

Figure 9: COMBINED, Mean-Return

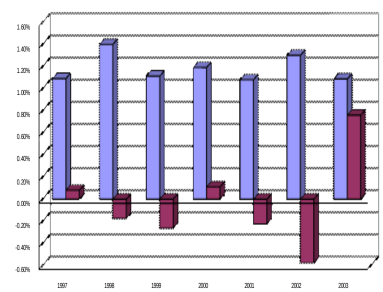

Figure 10: COMBINED, Sharpe-Ratio

4 Discussion

Three caveats are in oreder. First, on the selection of variables which constitute the universe of options available to the hypothetical investor in our simulations: three of the four variables used were previously found to be precisely the variables most highly correlated with the cross-section of ex post returns. The selection of beta as the fourth variable reduces the resulting bias in favour of predictability, but only (very) partially. Allowing for a realistically larger set of alternative variables which may have been considered, but did not prove so successful with hindsight, would reduce the bias. Second, we assumed zero trading costs. CGM find that evidence of predictability when the Sharpe ratio is used as the selection criterion is robust to the inclusion of trading costs, when the latter are estimated using the procedure due to Keim and Madhavan (1997). (Note, though, that alternative round-trip costs of 4 to 6% remove all evidence of real-time predictability.) In the present study, there is no statistically significant evidence of real-time predictability under any of the selection criteria, so adjusting for trading costs of any magnitude would only reinforce our results. (Trading costs in emerging markets are usually higher than in the more liquid US markets.) Thirdly, a recognized shortcoming of this study is the exclusion of delisted stocks. As the South African market matures and data availability improves, the application of a recursive out-of-sample methodology such as that of CGM to a dataset including delisted stocks would be fruitful.

Our findings do not refute previous research documenting in-sample CAPM anomalies. Indeed, we confirm in-sample predictability of the cross-section of South African stocks, and provide vivid illustrations of the ex-post profitability of trading strategies designed to exploit previously identified anomalies. Rather, our findings are an important caveat on the practical usefulness of the same anomalous variables in forming real-time investment portfolios. Thus, the study does not imply the South African stock market is "efficient." If the CAPM applies, and if it were correctly implemented in the same studies, then the evidence of anomalies (which the present paper confirms in-sample) is indicative of fundamental inefficiency – that is, prices deviate significantly from fundamental values. But profitably exploiting these deviations is not nearly as easy as implied for example in Fama and French (1992).

In an authoritative review article, Schwert (2003, p. 944-945, 948) presents a summary of the performance of prominent investment funds created to exploit scaled-price ratio and size effects documented in the empirical finance literature. For the first eight years since inception, the funds constructed to exploit scaled-price ratio effects (value portfolio) produced an average monthly excess return (relative to return predicted by the CAPM) of -0.2%; and the average excess returns from the small-company portfolio (exploiting the size effect) vary depending on sub-period, from -0.2 to 0.4% per month. (See CGM for further references on the inability of most fund managers to consistently out-perform passive indices.) In South Africa, an assessment of the performance of the main actively managed equity funds over the 1988 to 2003 period, finds that after adjusting returns for either costs or risk, a diversified market index outperforms the average of return of the active funds (Wessels and Krige (2005)). Such findings are not consistent with a stable and easily exploitable relationship between ex-post CAPM-anomalies and the cross-section of returns.

5 Concluding remarks

There is active research aimed at providing a theoretic foundation to momentum, size, and scaled-price ratio effects as determinants of returns. (See for example Shleifer (2000), Barberis and Thaler (2003), and Zhang (2005).) Yet, (i) there is evidence that the effect of size fluctuates over time, and declines or reduces towards the end of sample periods (Pastor (2000), Davis, Fama and

French (2000), Bossaerts and Fohlin (2000)); (ii) the evidence of scaled-price ratio effects differs across international data - for example, the book-to-market effect has opposite signs in US and German data (Bossaerts and Fohlin (2000)), and earnings-yield has a stronger effect in South Africa than book-to-market (Robertson and Van Rensburg (2004)); (iii) in certain markets, size and scaled-price ratio effects disappear when controlled for a calendar (January) effect (Hawawini and Keim (1998)), while calendar effects have been shown to be due to data mining bias (Sullivan, Timmermann and White (2001)); (iv) the size effect may reflect the mathematical relation between market values and rates of discount as argued by Berk (1995, 1997); (v) finding size and scaled-price ratio effects in a sample with only continuously listed shares can be theoretically explained by selection bias (Brown, Goetzmann and Ross (1995)); and lastly, (vi) returns from momentum portfolios follow mathematically from the cross-sectional dispersion in mean returns (Bossaerts (2002)).

This collection of empirical and theoretic results suggests that the large evidence of a systematic relationship between size and scaled-price ratios, with the cross-section of common stock returns, and of a momentum effect, is either spurious or unstable - explaining our finding that the in-sample predictability does not readily translate to profitable opportunities in real-time. If the relationship between momentum, size and scaled-price ratio effects, and the cross-section of common stocks, is unstable, the investor has to understand how these effects vary with changes in economic states, in order to trade profitably in real-time on the basis of the empirically identified factors.

6 Appendix

6.1 Appendix A

The return index, R, is calculated assuming dividends are reinvested to purchase additional units of the stock at the closing price applicable on the ex-dividend date:

$$R_t = R_{t-1} \left(P_t / P_{t-1} \right), \tag{3}$$

where R_t is the return index at t and P_t is the price at t. When t is the ex-dividend date the return index is computed as:

$$R_t = R_{t-1} \left(\left(P_t + D_t \right) / P_{t-1} \right), \tag{4}$$

where P_t is the price on ex-dividend date t and D_t is the dividend for period t.

6.2 Appendix B

Continuously compounded returns, $r_{i,t} = \log \left(P_{i,t} / P_{i,t-1} \right)$ are used throughout the paper. Hence the mean monthly return to rule i, $\overline{r_i}$, is computed as:

$$\overline{r_i} = \frac{1}{12} \left(\sum\nolimits_{t=1}^{12} r_{i,t} \right), \tag{5}$$

where $r_{i,t}$ is the monthly equally weighted return to rule i in month t.

The Sharpe ratio for rule i is computed as:

$$S_i = \frac{\overline{r_i} - r_f}{\sigma_i}, \tag{6}$$

where r_f is the mean monthly risk-free return and σ_i is the standard deviation of monthly returns to rule i.

CGM also used the terminal wealth criterion, computed as

$$T_i = \exp\left(\sum_{t=1}^{12} r_{i,t}\right), \tag{7}$$

where T_i is the value at the end of June t+1 of one South African rand invested according to trading rule i, at the beginning of July t. But note, from the definition of $r_{i,t}$, that terminal wealth T_i is equal to $\prod_{t=1}^{12} \frac{P_{i,t}}{P_{i,t-1}}$. Hence, using the definition of $\overline{r_i}$, we can obtain the mean monthly return from terminal wealth (or vice-versa) since $\overline{r_i} = \frac{1}{12}\log P_i$. Not surprisingly, we found that the mean-return and terminal-wealth simulations yield identical portfolio rule compositions (except for one period), and concentrate on the two criteria which identify different portfolios.[21]

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[21] In this period, two rules under consideration for both the mean-return and terminal-wealth SHORT portfolios were jointly ranked 59th based on their cumulative in-sample ranks. In the event of the ranking procedure failing to definitively select the best or worst-performing rules, the underlying figures are used to differentiate between the jointly ranked rules. The two criteria differed with respect to the rule selected on the basis of the actual figures. However, in light of the extremely marginal difference for rule selection in this instance, it was deemed sufficient to consider the rule selections as identical.

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